

Decomposition of productivity considering multi-environmental pollutants in Chinese industrial sector

Hidemichi Fujii

Graduate School of Environmental Studies, Tohoku University

6-6-20 Aramaki-Aza-Aoba, Aoba-ku, Sendai, 980-8579 Japan.

E-mail: hidemichifujii@gmail.com / Phone: +81-22-795-3217 / Fax: +81-22-795-4309

Jing Cao

School of Economics and Management, Tsinghua University

Beijing 100084, China.

E-mail: caojing@sem.tsinghua.edu.cn / Tel +86(10) 62792726 / Fax +86(10) 62785562

Shunsuke Managi*

Graduate School of Environmental Studies, Tohoku University

6-6-20 Aramaki-Aza-Aoba, Aoba-ku, Sendai, 980-8579 Japan.

E-mail: managi.s@gmail.com / Tel +81(22) 795 3216 / Fax +81(22) 795 4309

*Corresponding author.

ABSTRACT

The objective of this study is to calculate and decompose productivity incorporating multi-environmental pollutants in Chinese industrial sectors from 1992 to 2008. We apply a weighted Russell directional distance model to calculate productivity from both the economic and environmental performance. Main findings are, 1) Chinese industrial sectors increased productivity, with the main contributing factors being labor saving prior to 2000. 2) The main contributing factors for productivity growth in coastal areas include both economic and environmental performance improvement. While central and west regions improved productivity due to economic development, they have a trade-off relationship between economic and environmental performance.

I. Introduction

Since 1990, the economic development of China has produced an average 10.2% growth rate and it is forecast that this rapid upward trend in economic growth will continue. Along with such impressive economic development and rapid industrialization, many environmental problems have arisen, including industrial pollution, which has attracted much attention (Zhang *et al.*, 2010).

Productivity improvement is the main driver of economic growth, but rapid growth can increase pollutant emissions due to the greater use of resources. Consequently, there is a conflict between economic growth and environmental concerns. In research on growth theory, analyses of economic growth and the environment have shown the importance of productivity increases and found that improved productivity decreases the input demand for pollution levels (Akao and Managi, 2007). Thus, emission reductions should be considered for continuous productivity progress.

There are a few Chinese studies on productivity considering environment. Fujii *et al.* (2011) apply directional distance function and Luenberger productivity indicator to estimate productivity change considering wastewater and CO₂ emissions in iron and steel firms. Wang *et al.* (2008a) applied the Malmquist-Luenberger index method to measure the total

productivity change, including carbon emissions as undesirable outputs, for 17 APEC countries and regions for 1980-2004. Hu *et al.* (2008) use the Malmquist index to rank the provincial Total Factor Productivity (TFP) when incorporating environmental factors for 1999-2005. Cao (2007) uses a time-series input-output table, and measures the Green TFP using estimated health damages from undesirable pollutions following the Jorgenson Divisia index method.

This study measures productivity change in Chinese industrial sectors by provinces. We apply the weighted Russell directional distance model (WRDDM) to measure productive inefficiency using production technology following Chen *et al.* (2011) and Barros *et al.* (2011). They proposed a measure based on directional distance function, which is evaluated in linear form, and hence processes the attractive advantages of easy computation and easy extension of incorporating the additional undesirable outputs into the programming problems. Our main objective is to estimate the contribution of each input/output considering environmental pollutions in Chinese industrial sector. Those points are not considered in the previous study. We further apply nonparametric test for equality densities by Li et al. (2009) to understand the difference of TFP differences.

The rest of this paper is organized as follows. In Section 2, we explain environmental

pollution problem from industrial sector and environmental policy in China. In Section 3, we introduce our methodology – weighted Russell directional distance model, and the decomposition methods of productivity change. Using China's provincial panel data from 1992-2008, we analyze the productivity change considering environmental pollution in Chinese industrial sectors in Section 4. Section 5 presents our conclusion and discusses the policy implications.

II. Environmental Pollution from Chinese Industrial Sector

Facing the bottleneck of sustainable development, China has identified air pollution as a high-priority issue that it must address immediately (Managi and Kaneko, 2010). China became the world's largest sulfur dioxide (SO_2) emitter in 2005 (Su et al., 2011), and it is now evident that many of the existing air pollution problems are the result of these significant SO_2 emissions. According to You and Xu (2010), economic losses due to acid rain and acid deposition in China amounted to 176.42 billion yuan in 2000, which is 1.97% of China's gross domestic product. After joining the WTO in 2001, China has gradually become a world factory for manufacturing commodities (Hoa, 2010). According to Auffhammer and Carson (2008), China is now the biggest carbon emitter in the world, surpassing the U.S. in 2006, and

releasing about 6.9 billion tons of CO₂ emissions in 2009.

Furthermore, industrial sectors discharge large amounts of soot and dust substances into the air. Because of these serious air pollution problems, twenty Chinese cities were listed among the world's thirty most polluted cities (World Bank, 2007). These air pollution problems cause severe health damages in the human respiratory and cardiovascular systems, increasing incidences of premature mortality, as well as hospital admissions and outpatient visits (Kan and Chen, 2004; Wang and Mauzerall, 2006; Levy and Greco, 2007). According to the Ministry of Health data, the mortality rate from respiratory diseases in China is over 17%, making it the third largest killer after circulatory disease and cancer (Ministry of Health, 2008), whereas the world average mortality rate from respiratory diseases is less than 8% (WHO, 2011). The World Bank estimates that 13% of all urban premature deaths may be due to ambient air pollution. The overall health damage due to air pollution is roughly 3.8% of GDP in China (World Bank 2007, 2009). Because SO₂ particulate matters are the main air pollution substances that cause respiratory diseases in China, it is critical that the emission of these pollutants be reduced so as to improve the overall condition of people's health (Xie *et al.*, 2005).

Meanwhile, water pollution by industrial wastewater is another big problem in China,

especially in the northern part of China, where the water resource shortage problem is severe (Wang *et al.*, 2008b). Pollution levels are particularly high for ammonia nitrogen, dissolved oxygen, BOD and permanganate, roughly 17%-33% of monitoring sites not meeting class III drinking water standards. Among the 27 major lakes and reservoirs monitored in 2004, none met the Grade I water quality standard, and only two met the Grade II water quality standard (World Bank, 2007). To solve water pollution problems, the Chinese government has enforced more strict environmental regulations and a levy system to promote wastewater management in Chinese industrial sectors (see Table 1). According to Shao (2010), the Chinese government has enacted more than 130 policies related to environmental protection since 1979 to curb the deterioration of water environments and to improve the surface water quality.

< Table 1. about here >

Table 1 provides a summary of China's major environmental policies covering the last three decades. Environmental protection has become one of the high priority targets for the Chinese government. In China's ninth five-year plan, the Chinese government enforced a strong environmental policy to decrease industrial pollution. For instance, China forced more than

80,000 small, polluted enterprises in 15 heavy-polluting industries to shut down or stop production lines during 1997-2000 (Zhang and Wen, 2008).

In the 11th five year plan, the Chinese government has implemented more stringent energy conservation and pollution control targets during 2006-2010. For example, China's energy intensity is required to be reduced by 20%; that is, energy intensity per 10,000 yuan GDP should decline from 1.22tce in 2005 to 0.98tce in 2010. Water consumption per unit of industrial value-added is required to be reduced by 30%, and COD and SO₂ emissions are required to be reduced by 10% from the benchmark year 2005. Additionally, the government has promoted industrial sectors to produce more environmentally production equipment, for instance to install flue gas desulfurization (FGD) equipment on new and existing coal-fired power plants, and shutdown 50GW inefficient and highly polluting small power plants.

Figure 1 shows that wastewater, waste gas, and solid waste discharge amount from industrial sectors in China from 1992 to 2008. Even though many environmental regulations and policies were enforced, environmental pollution has rapidly increased since 2000, especially waste gas and solid waste (see Figure 1). This pollution increase was mainly due to the rapidly expanding production scale in China after China's WTO entry. Pollution per value-added (Environmental efficiency) has been improved between 1992 and 2008.

Wastewater, waste gas, and solid waste emissions per value added decreased by more than 80%, 40%, and 60% respectively, during this period.

< Figure 1. about here >

III. Methodology

A. Weighted Russell Directional Distance Model (WRDDM)

Weighted Russell directional distance model (WRDDM) is developed by Chen *et al.* (2011) and Barros *et al.* (2011). Let inputs be denoted by $x \in R_+^N$, good outputs by $y \in R_+^M$, and bad or undesirable outputs by $b \in R_+^L$. The directional distance function seeking to increase the desirable outputs and decrease the undesirable outputs and inputs directionally can be defined by the following:

$$\vec{D}(x, y, b|g) = \sup\{\beta: (x + \beta g_x, y + \beta g_y, b + \beta g_b) \in T\} \quad (1)$$

Where the vector $g = (-g_x, g_y, -g_b)$ determines the directions in which inputs, desirable outputs, and undesirable outputs are scaled. The vector specifies for inefficient samples the

way to improve productivity towards the frontier production line. The technology reference set $T = \{(x, y, b): x \text{ can produce } (y, b)\}$ satisfies strong disposability of desirable outputs and inputs, and weak disposability of undesirable outputs.

Suppose there are $j = 1, 2, \dots, k, \dots, J$ decision-making units (DMUs) in the dataset. Each DMU uses inputs $x = (x_1, x_2, \dots, x_N) \in R_+^N$ to jointly produce desirable outputs $y = (y_1, y_2, \dots, y_M) \in R_+^M$ and undesirable outputs $b = (b_1, b_2, \dots, b_L) \in R_+^L$. Following Aparicio et al. (2013) and Fujii et al. (2014), the WRDDM for inefficiency calculation with variable returns to scale of DMU k can be described as follows:

$$\vec{D}(x, y, b|g) = \text{maximize} \left(\frac{1}{N} \sum_{n=1}^N \beta_n^k + \frac{1}{M} \sum_{m=1}^M \beta_m^k + \frac{1}{L} \sum_{l=1}^L \beta_l^k \right) \quad (2)$$

subject to

$$\sum_{j=1}^J z_k y_{mj} \geq y_{mk} + \beta_m^k g_{ymk} \quad (3)$$

$$\sum_{j=1}^J z_k b_{lj} = b_{lk} + \beta_l^k g_{blk} \quad (4)$$

$$\sum_{j=1}^J z_k x_{nj} \leq x_{nk} + \beta_n^k g_{xnk} \quad (5)$$

$$\sum_{j=1}^J z_k = 1 \quad (6)$$

$$Z_j \geq 0, \quad j = 1, 2, \dots, k, \dots, J \quad (7)$$

where β_m^k , β_l^k , and β_n^k are the individual inefficiency measures for desirable outputs, undesirable outputs, and inputs, respectively. Z_k is the intensity variable to shrink or expand the individual observed activities of DMU k for the purpose of constructing convex combinations of the observed inputs and outputs. To estimate productivity change indicators, we set directional vector = $(g_{xnk}, g_{ymk}, g_{blk}) = (-x_{nk}, y_{mk}, -b_{lk})^1$. This type of directional vector assumes that an inefficient province can decrease productive inefficiency while increasing desirable outputs and decreasing undesirable outputs and/or inputs in proportion to the initial combination of actual inputs and outputs.

One of the strong points of the WRDDM is that it is able to determine the effect of each variable's contribution to inefficiency. This contribution effect cannot be determined in conventional productive inefficiency analysis. The contribution effects enable us to discuss how and why each province successfully decreased its productive inefficiency. Under this vector combination, the WRDDM with variable returns to scale is shown as follows:

¹ We note that solution on for inefficiency depends simultaneously on all the observed inputs, outputs and bad outputs with weights of province estimated by WRDDM. Any interpretation of these coefficients has to be conditional on the input and output data for the industrial sector of each province under consideration represented by (x_{nk}, y_{mk}, b_{lk}) .

$$\vec{D}(x_k, y_k, b_k | g) = \text{maximize} \left(\frac{1}{N} \sum_{n=1}^N \beta_n^k + \frac{1}{M} \sum_{m=1}^M \beta_m^k + \frac{1}{L} \sum_{l=1}^L \beta_l^k \right) \quad (8)$$

subject to

$$\sum_{j=1}^J z_k y_{mj} \geq y_{mk} (1 + \beta_m^k) \quad (9)$$

$$\sum_{j=1}^J z_k b_{lj} = b_{lk} (1 - \beta_l^k) \quad (10)$$

$$\sum_{j=1}^J z_k x_{nj} \leq x_{nk} (1 - \beta_n^k) \quad (11)$$

$$\sum_{j=1}^J z_k = 1 \quad (12)$$

$$Z_j \geq 0, \quad j = 1, 2, \dots, k, \dots, J \quad (13)$$

One of the strong points of the WRDDM is that it is able to determine each variable's contribution effect for inefficiency. This contribution effect cannot be determined in conventional productive inefficiency analysis. The contribution effects enable us to discuss how and why each province successfully decreased its productive inefficiency.

B. TFP Change Estimation and Decomposition

In order to analyze changes in efficiency over time, aggregated indices such as the *Malmquist Index* and *Luenberger Productivity Indicator* have been developed (Chambers, 1998). They are derived from the efficiency scores of production frontier models. These productivity indices are measures of total factor productivity (TFP), when the efficiency score comes from economic production frontier models. TFP includes all categories of productivity changes and can be decomposed further to provide a better understanding of the relative importance of various components, including *Technical change* and *Efficiency change* (Färe *et al.*, 1994). *Technical change* measures shifts in the production frontier, so-called frontier shift. *Efficiency change* measures changes in the position of a production unit relative to the frontier, the so-called catching-up factor.

We employ the *Luenberger Productivity Indicator* as a TFP measure because the *Luenberger Productivity Indicator* has advantage for productivity change estimation with additive distance function model than Malmquist productivity index (Balk *et al.*, 2008). Change in the *Luenberger Productivity Indicator* (TFP) is further decomposed into technical change and efficiency change². TFP is computed with the results of the WRDDM and derived as follows:

² O'Donnell (2012) and Diewert and Fox (2012) pointed out the mix and scale efficiency are key component to determine the TFP for industrial sector. Scale efficiency and mix efficiency can be estimate by using index approach such as data envelopment analysis. Meanwhile, this study employ weighted Russell directional distance model, which does not use index approach but distance function, have difficult to estimate mix and scale efficiency. This point is our research limitation.

$$TFP_t^{t+1} = \frac{1}{2} \{ \vec{D}^{t+1}(x_k^t, y_k^t, b_k^t) - \vec{D}^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) + \vec{D}^t(x_k^t, y_k^t, b_k^t) - \vec{D}^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) \} \quad (14)$$

$$TECHCH_t^{t+1} = \frac{1}{2} \{ \vec{D}^{t+1}(x_k^t, y_k^t, b_k^t) + \vec{D}^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) - \vec{D}^t(x_k^t, y_k^t, b_k^t) - \vec{D}^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) \} \quad (15)$$

$$EFFCH_t^{t+1} = \vec{D}^t(x_k^t, y_k^t, b_k^t) - \vec{D}^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) \quad (16)$$

$$TFP_t^{t+1} = TECHCH_t^{t+1} + EFFCH_t^{t+1} \quad (17)$$

where x_t represents the input for year t , x_{t+1} is the input for year $t+1$, y_t is the desirable output for year t , and y_{t+1} is the desirable output for year $t+1$. b_t is the undesirable output for year t , and b_{t+1} is the undesirable output for year $t+1$. $\vec{D}^t(x_k^t, y_k^t, b_k^t)$ is the inefficiency score of year t based on the frontier curve in year t . Similarly, $\vec{D}^{t+1}(x_k^t, y_k^t, b_k^t)$ is the inefficiency of year t based on the frontier curve in year $t+1$.

We obtain aggregated TFP from technological and efficiency changes from (14) – (17) where all components of directional distance functions are estimated by (8) – (13). The TFP score indicates the productivity change as compared to the benchmark year. The TFP includes all categories of productivity change, which can be broken down into Technical Change (TECHCH) and Efficiency Change (EFFCH). TECHCH shows shifts in the production frontier, while EFFCH measures changes in the position of a production unit relative to the

frontier.

Here, we decompose TFP using the inefficiency score of each variable's contribution effect for inefficiency. Let us describe the each variable's contribution effect for inefficiency as follows.

$$\text{maximize } \left(\frac{1}{N} \sum_{n=1}^N \beta_n^k + \frac{1}{M} \sum_{m=1}^M \beta_m^k + \frac{1}{L} \sum_{l=1}^L \beta_l^k \right) = \vec{D}_x(x_k^t, y_k^t, b_k^t) + \vec{D}_y(x_k^t, y_k^t, b_k^t) + \vec{D}_b(x_k^t, y_k^t, b_k^t) \quad (18)$$

Where $\vec{D}_x(x^t, y^t, b^t)$ represents the contribution effect of input variables for inefficiency score, $\vec{D}_y(x, y, b)$ represents the contribution effect of desirable output variables for inefficiency score, and $\vec{D}_b(x, y, b)$ represents the contribution effect of undesirable output variables for inefficiency score. Then, we can obtain following equation:

$$\vec{D}^t(x_k^t, y_k^t, b_k^t | g) = \vec{D}_x^t(x_k^t, y_k^t, b_k^t) + \vec{D}_y^t(x_k^t, y_k^t, b_k^t) + \vec{D}_b^t(x_k^t, y_k^t, b_k^t) \quad (19)$$

From equation (14) and (18), we have the following TFP decomposition form:

$$\begin{aligned} \text{TFP}_t^{t+1} &= \frac{1}{2} \{ \vec{D}^{t+1}(x_t, y_t, b_t) - \vec{D}^{t+1}(x_{t+1}, y_{t+1}, b_{t+1}) + \vec{D}^t(x_t, y_t, b_t) - \vec{D}^t(x_{t+1}, y_{t+1}, b_{t+1}) \} \quad (20) \\ &= \frac{1}{2} \{ \vec{D}_x^{t+1}(x^t, y^t, b^t) - \vec{D}_x^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_x^t(x^t, y^t, b^t) - \vec{D}_x^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \end{aligned}$$

$$\begin{aligned}
& + \frac{1}{2} \{ \vec{D}_y^{t+1}(x^t, y^t, b^t) - \vec{D}_y^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_y^t(x^t, y^t, b^t) - \vec{D}_y^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \\
& + \frac{1}{2} \{ \vec{D}_b^{t+1}(x^t, y^t, b^t) - \vec{D}_b^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_b^t(x^t, y^t, b^t) - \vec{D}_b^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \\
& = \text{TFP}_{t,x}^{t+1} + \text{TFP}_{t,y}^{t+1} + \text{TFP}_{t,b}^{t+1}
\end{aligned}$$

Where $\text{TFP}_{t,x}^{t+1} = \frac{1}{2} \{ \vec{D}_x^{t+1}(x^t, y^t, b^t) - \vec{D}_x^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_x^t(x^t, y^t, b^t) -$

$\vec{D}_x^t(x^{t+1}, y^{t+1}, b^{t+1}) \}$,

$\text{TFP}_{t,y}^{t+1} = \frac{1}{2} \{ \vec{D}_y^{t+1}(x^t, y^t, b^t) - \vec{D}_y^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_y^t(x^t, y^t, b^t) - \vec{D}_y^t(x^{t+1}, y^{t+1}, b^{t+1}) \}$,

$\text{TFP}_{t,b}^{t+1} = \frac{1}{2} \{ \vec{D}_b^{t+1}(x^t, y^t, b^t) - \vec{D}_b^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_b^t(x^t, y^t, b^t) - \vec{D}_b^t(x^{t+1}, y^{t+1}, b^{t+1}) \}$ (21)

where $\text{TFP}_{t,x}^{t+1}$ represents a contribution effect of input variables for TFP change. $\text{TFP}_{t,y}^{t+1}$ represents a contribution effect of desirable output variables for TFP change. $\text{TFP}_{t,b}^{t+1}$ represents a contribution effect of undesirable output variables for TFP change. Here we explain the meaning of contribution effect change by using $\text{TFP}_{t,x}^{t+1}$. Increasing of $\text{TFP}_{t,x}^{t+1}$ is caused by following two cases. In the first case, contribution effect of input variables is improved. In this case, we can understand $\text{TFP}_{t,x}^{t+1}$ growth represents how much TFP increases due to improvement of input use.

In the second case, inefficiency of input becomes smaller than inefficiency of desirable

output or undesirable output. This case shows that inefficiency of input improves rapidly relative to desirable output or undesirable output. In this case, $TFP_{t,x}^{t+1}$ will increase and $TFP_{t,y}^{t+1}$ or $TFP_{t,b}^{t+1}$ decrease. This is because WRDDM evaluates each variable's contribution effect (such as $\vec{D}_x^t(x^t, y^t, b^t)$) by maximizing relative inefficiency among input, desirable output, and undesirable output. Therefore, we need to check carefully why each contribution effect of TFP change is changed, especially focusing on the substitution of contribution effects of each variable. From equation (15), (16), and (20), we can also decompose the TECHCH indicator and EFFCH indicator by the following decomposition formula:

$$TECHCH_t^{t+1} = TECHCH_{t,x}^{t+1} + TECHCH_{t,y}^{t+1} + TECHCH_{t,b}^{t+1} \quad (22)$$

$$EFFCH_t^{t+1} = EFFCH_{t,x}^{t+1} + EFFCH_{t,y}^{t+1} + EFFCH_{t,b}^{t+1} \quad (23)$$

C. Technological Innovation

It should be noted that the technical progress change index for any particular state between two adjacent years merely depicts the shift in the production frontier for that province. A value of technical change index greater than unity does not necessarily imply that the province under consideration did actually push the frontier outward. Thus in order to

determine the provinces that were shifting the frontier or were “innovators” (see Färe *et al.*, 1994), the following three conditions are required to be fulfilled for a given province:.

$$(a) \text{ } TECHCH_t^{t+1} > 0 \quad (24)$$

$$(b) \vec{D}^t(x^{t+1}, y^{t+1}, b^{t+1}) < 0 \quad (25)$$

$$(c) \vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) = 0 \quad (26)$$

The condition (a) indicates that the production frontier shifts in case of more desirable outputs or less undesirable output for the given level of input. With a given input vector, in period t+1 it is possible to increase desirable output or decrease undesirable output relative to period t. This measures the shift in the relevant portions of the frontier between periods t and t+1 for a province. The condition (b) indicates the production in period t+1 that occurs outside the frontier of period t (i.e., technical change has occurred). It implies that the technology of period t is incapable of producing the desirable output vector of period t+1 and undesirable output vector of period t+1 with the input vector of period t+1. Hence, the value of output distance function $(x^{t+1}, y^{t+1}, b^{t+1})$ relative to the reference technology of period t is greater

than one. The condition (c) specifies that the province must be on the production frontier in period $t+1$.

By using the WRDDM result, we can distinguish the technological innovator from the economic and environment point of view. Technological innovator of economic performance need to fulfill the following conditions. The technological innovator of economic performance ($\text{Innovator}_{\text{Econ}}$) achieves more efficient input use and value added production from t year to $t+1$ year:

$$(d) \text{TECHCH}_{t,x}^{t+1} + \text{TECHCH}_{t,y}^{t+1} > 0 \quad (27)$$

$$(e) \vec{D}_x^t(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_y^t(x^{t+1}, y^{t+1}, b^{t+1}) < 0 \quad (28)$$

$$(f) \vec{D}_x^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_y^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) = 0 \quad (29)$$

Additionally, the technological innovators of environmental performance need to fulfill the following conditions. The technological innovator of environmental performance ($\text{Innovator}_{\text{Env}}$) achieves more efficient environmental pollutant emissions management from t year to $t+1$ year.

$$(g) \text{TECHCH}_{t,b}^{t+1} > 0 \quad (30)$$

$$(h) \vec{D}_b^t(x^{t+1}, y^{t+1}, b^{t+1}) < 0 \quad (31)$$

$$(i) \vec{D}_b^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) = 0 \quad (32)$$

IV. Result

A. Data

To understand the differences of regional characteristics, we make three groups which is coastal, central and western area. Coastal area includes Beijing, Tianjin, Shandong, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Central area consists of Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. Finally, Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Inner Mongolia, Guangxi, and Xinjiang are located in the western area. Tibet is excluded because some relevant data are not available. Data for Chongqing, which was separated from Sichuan in 1997, is merged with data for Sichuan. Thus, our data sample is 29 provinces over 1992 to 2008³.

Data for the study were collected from two main sources: the China Environmental

³ This study only uses provincial level data but not firm level data. This is because firm level data is difficult to correct capital stock data and pollution data. As the composition of industrial sector differs significantly across different provinces, use of a simple measure of value added ignores the role of composition in the production of environmental pollutants. Currently, there is not such composition data available in Chinese province database.

Statistical Yearbook (CESY) and the China Statistical Yearbook (CSY). The data covers the seventeen year period from 1992 to 2008. The main variables used in the analysis are value added (yuan) as desirable output⁴; amount of labor (number of persons) and net value of fixed assets (yuan)⁵ as market input; wastewater discharge amount (tonnes), waste gas emissions (m³), and solid waste discharge amount (tonnes) as the undesirable output. We consider the wastewater, waste gas, and solid waste emissions are major and important measure to evaluate industrial environmental performance and many previous studies use these three variables (e.g. Managi and Kaneko, 2010). All financial data variables are deflated as 1995 year price⁶.

CESY does not cover the entire sample collected in the CSY. Thus, data coverage in the CESY is different with that in CSY. Therefore, productivity estimation using both CSY and CESY data directly is not consistent because of the mismatch of data coverage. To overcome this problem, we adjust the data from CESY so as to be able to compare the data to the CSY. Sales data are included in both the CESY and the CSY. Therefore, we calculate an adjustment coefficient by taking the ratio of sales data in the CESY and that in the CSY⁷. We then

⁴ Because intermediate input data is not available, we use labor and capital data as input. In this case, total revenue and total production data are not consistent to use as desirable output data. Thus, we use value added data which is calculated by total revenue minus intermediate cost.

⁵ We estimate capital stock data using net value of fixed asset is taken from China Industry Economy Statistical Yearbook. Net value of fixed assets in current price and therefore only Perpetual Inventory Method can add them up correctly by deflating them in different price level. However, there is no industrial depreciation ratio data and price index of fixed capital by province in China. Thus, we consider net value of fixed assets as capital stock data. Because we apply time series analysis in this study, we need to deflate monetary data to understand the productivity change score. To satisfy this condition, we deflate monetary data using provincial retail price index which is data openly available on the China Statistical Yearbook. Those points are limitation of study.

⁶ Following Managi and Kaneko (2009), we use the price index to deflate all monetary data variable is retail price index.

⁷ We use sales data for adjustment because we have difficulty to correct the product amount data by type of product. Therefore, the sales data was used to determine the production amount. Generally, the amount of pollutant emissions depended upon the input amount of fossil energy and intermediate chemical materials. This is because the production scale became a factor in determining pollutant emissions.

multiply the adjustment coefficients to expand the data coverage of CESY, which vary by year and province⁸. This adjustment technique follows procedures by Managi and Kaneko (2009).

In this study, all pollutants data from CESY is expanded by using adjustment coefficient. Estimated pollution data (E_{adj}) is calculated as $E_{jt,adj} = SALE_{jt,CESY} \times (E_{jt,CESY} / SALE_{jt,CESY})$ by using emission data from CESY (E_{CESY}), sale data from CESY ($SALE_{CESY}$) and sale data from CSY ($SALE_{CSY}$) in province j year t . We apply this data expansion approach for wastewater emissions, waste gas emissions, and solid waste emissions data, separately.

B. Productivity Change and Contribution Effect

Figure 2 represents the provincial average inefficiency score from 1992 to 2008, where provincial names are described in Appendix 1. Tianjin, Shanghai, Shandong, Guangdong, and Hainan have zero inefficiency in Figure 2, which shows that the production performance of manufacturing sectors in these five provinces are efficient from 1992 to 2008. Additionally, Beijing, Heilongjiang, Yunnan, and Qinghai have low inefficiency scores, suggesting they also achieved efficient performance in our examined time-range. Thus, the production frontier

⁸ Industrial structure is important factor for amount of pollutants associated with a given level of sales. However, we have difficulty to correct entire pollutant emissions data by industry in each province. Thus, we apply data expansion approach using adjustment coefficient calculated by sales data. In this data expansion approach, we assume data coverage of CESY reflects the industrial structure of whole industrial sector in province. Additionally, we have another assumption that the industrial firm which is not covered in sample data has same pollution abatement technology with the industrial firms covered in sample data. Under these two assumptions, we can use expanded pollution data with economic data for production function approach. This point is limitation of this study.

line of Chinese manufacturing sectors mainly consists of these nine provinces.

<Figure 2. about here>

Figure 3 through Figure 5 show the accumulative changes of TFP, TECHCH, and EFFCH indicators from 1992 to 2008. We set 1992 as the baseline year, then the three indicators equal zero in 1992. A positive TFP score indicates that a Chinese industrial sector achieved productivity improvement. In Figure 3 through Figure 5, the line chart indicates the accumulative 29 provincial average score of TFP, TECHCH, and EFFCH indicators compared in 1992. And the bar chart shows the accumulative contribution effect of each factor with respect to the TFP, TECHCH, and EFFCH change. The results as indicated in the bar chart are equal to those in the line chart. To compare the results in each Figure, we can distinguish the main contributor for TFP, TECHCH, and EFFCH change according to the individual pollutant and economic variables.

Then, we consider the result of productivity change. According to Figure 3, the Chinese industrial sector increases TFP by nearly 40% from 1992 to 2008. The rapid TFP increase

from 1992 to 1993 and decline after 1993 are caused by price deregulation policy in China⁹.

After 1995, TFP increases again and the main contributors are labor force saving, value added increase, and environmental pollution managements. Contribution effect from Labor force saving mainly affects TFP to increase in 1990's and early 2000's. Figure 3 shows contribution effect of capital input has a negative effect on TFP change from 1997. From these two results, we suppose that the Chinese manufacturing sector increases TFP by utilizing modern production equipment that allows production input substitution from labor force to capital equipment.

In Figure 3, the contribution effect of value added has a negative effect on TFP in the 1990's, which is caused by the performance of inefficient provinces. This is because value added factor has a significantly negative effect on EFFCH indicator in Figure 5, which shows that the inefficiency gap between efficient and inefficient province becomes larger due to the slow speed of value added increase in inefficient provinces. One interpretation of this result is that, differences of production technology are affected by the technological spillover from

⁹ Chinese government implemented the price deregulation policy from 1992 into manufacturing product, especially steel product price. This price deregulation affected the performance in China's manufacturing sectors. The price of manufacturing products rapidly increased after price deregulation. Wire rod, for example, was 1,600 Yuan per ton in February 1992 before the policy change, but immediately after the change in April 1992, the price increased to 1,750 Yuan per ton. Wire rod reached 3,500 Yuan per ton in December 1992, meaning the price more than doubled within a year. Although the price of steel continued to increase during 1993, it started declining in late 1993 and bottomed at 2,000 Yuan per ton in December 1993 (Yearbook of Iron and Steel Industry of China, 1994, 1995).

developed countries through the foreign direct investment (FDI). Regional distribution of FDI is diversified in China, and the main FDI target is the coastal areas which have easy access to international trade. So, high-technology and high-profit ratio manufacturing sectors (e.g. electric products, precision equipment) are developed in coastal areas even though west and central provinces mainly produce conventional manufacturing sectors (e.g. mining sector). We support this situation reflecting value added gap between efficient provinces (mainly coastal area) and inefficient provinces (mainly central and west area).

We do not observe this negative effect of value added factor except 1995 for TECHCH indicator in Figure 4, which suggests the value added keep increasing year by year in efficient provinces. Thus, the negative effect of value added into TFP is caused by low profitable performance in inefficient provinces in the late 1990's.

After 2000, the contribution effect of value added positively affected China's TFP improvement. China's WTO entry in 2000 stimulated a massive expansion of export-oriented manufacturing sectors. China's labor-intensive manufacturing has achieved a comparative advantage on a global scale, and the size of the production scale further improved the production efficiencies. China also includes a GDP target of 7-7.5% in the 10th, 11th and 12th Five year Plan, and very few provinces report GDP growth lower than this plan target, as local

government officer's promotion is closely linked with such GDP target, thereby achieving an aggregate GDP growth at 10.1% for the period of 2000-2010 (NBS, 2011).

Another interpretation of this result is that the Chinese government set the political target and provided certain preferred policies for promoting high-technology industry that produces high profit ratio products in China's Tenth Five-Year Plan (for 2001 through 2005). For instance, the Chinese government increased the value added tax and consumption rebates on high-tech commodity exports, mostly around 13%-16%, thereby increasing the comparative advantages on these products. High-tech industries also enjoyed preferred treatment on tax payments, such as reducing enterprise income tax from 25% to 15%.

Contribution effects of industrial wastewater managements also contribute improving TFP gradually from 1992 to 2008 in Figure 3. From Figure 4, the TECHCH indicator rapidly increased from 2004 due to industrial wastewater management effects. Meanwhile the EFFCH indicator dramatically decreased after 2004 due to the shift in the production frontier line from Figure 5. This result is caused by a rapid decrease in pollutant emission, especially wastewater discharge, in Shanghai, which creates a production frontier line. Thus, rapid industrial wastewater reductions in Shanghai contributed to the increase in the TECHCH indicator. At the same time, EFFCH indicator decreases due to the gap of environmental

pollutant management in this period because other inefficient provinces do not catch up the reduction speed in Shanghai. Shanghai spent about 3% of GDP on environmental investment, setting up “non-coal-using” zones, phasing out inefficient public and taxi vehicles, helping to reduce particulate matters by 25% in 2004¹⁰. Shanghai also improved efficiency on wastewater treatment through marketization of urban water infrastructure with public-private joint venture approach, along with huge subsidies on the service fee and preferential policies (e.g. providing free or cheaper land to the investor) (Zhong et.al, 2008). While in other provinces, due to the expansion of manufacturing and rising fossil fuel demand, many local governments failed to achieve the 10th Five Year Plan targets on environmental protection.

<Figure 3, 4, 5 about here>

C. Comparison of Regional Characteristics of TFP, Contribution Effect, and Innovator

In this section, we discuss the regional differences of TFP change and innovators of

¹⁰ <http://www.sepb.gov.cn/fa/cms/shhj/shhj2143/shhj2144/2005/03/7556.htm>

technological frontier. Table 2 and Table 3 show accumulated TFP change and contribution effect of each variable by region from 1992 to 2008. We also show the result of testing equality of multivariate densities in Table 2 and Table 3 to test the statistical differences between each TFP indicators among regions. This study used nonparametric methods to obtain TFP and contribution effects. In this case, we are not able to know the distribution of score in advance and, therefore, we need to apply the nonparametric equality test called nonparametric test for equality densities which was introduced by Li et al. (2009). This nonparametric equality test would be best to analyze the difference of distribution when analyzing TFP and contribution effects. This equality testing employ bootstrap resampling to obtain the finite-sample distribution of the statistic. In this paper, we set the bootstrap algorithm was repeated 1,000 times.

From Table 2, coastal areas more rapidly increase TFP than central and west regions from 1992 to 2008. TFP_b scores in coastal areas are much higher than those in west and central areas. Another finding is that, the contribution effect of labor increase more rapidly in coastal areas than in others. This result implies two situations: (1) industrial structure in coastal areas shifted faster from labor intensive industry (conventional sector) to capital intensive industry (modern and high-technology industry) than other region, (2) coastal areas successfully

improve labor productivity by inducing modern production equipment (input substitution effect). These results show that central and west region achieved more rapid value added increasing than coastal area from 1992 to 2008. One interpretation of this result is that there is large gap of profitability performance between coastal area and the other regions at the initial condition (1992 year) because coastal area produce high-tech product while west and central region are mainly produce conventional product (e.g. textile, wood product) .

< Table 2. about here>

Table 3 represent how many times provinces in each area become technological innovator by economic point of view ($\text{Innovator}_{\text{Econ}}$), environmentally point of view ($\text{Innovator}_{\text{Env}}$), and both point of view (Innovator). We also show the accumulated FDI, accumulated patent application, and accumulated patent granted from 1992 to 2008. Technological innovations in both economic and environmental performance mainly occurred in coastal provinces. Technological innovation mainly occurred through new technology invention, which is reflected by patent application or patents granted. From Table 3, both patent application and patents granted are higher in coastal areas than in others. One interpretation of this difference

is the regional distribution gap of FDI. FDI has an important role to promote patent invention and technological innovation in developing countries (Managi and Bwalya, 2010). Thus, the technological innovation in coastal areas might occur due to the FDI from developed countries.

<Table 3. about here>

Figure 6 shows the scatter plot of accumulated TFP_b and TFP_y+TFP_x by province. The first quadrant in Figure 6 represent achievement both economic and environmental performance improvement. While, the second and fourth quadrant represent trade-off relationship between environmental and economic performance. From Figure 6, many coastal provinces achieved combined improvement in economic performance and environmental performance from 1992 to 2008. Meanwhile, west area provinces show a trade-off relationship between economic performance and environmental performance. This trade-off relationship needs to reconcile the Western China Development and local environmental protection.

< Figure 6. about here>

V. Conclusion

This study analyzes productivity change relative to environmental pollution in Chinese industrial sectors from 1992 to 2008. Based on an empirical analysis, the major findings can be summarized as follows: First, Chinese industrial sectors succeeded in increasing productivity. The main contributing factors are industrial wastewater emissions reduction in coastal areas, and economic performance improvement in the central and west regions. Second, Chinese industrial TFP increased by 40% from 1992-2008. The main contributing factors are labor saving and value-added increase. After 2000, industrial wastewater management began to contribute more to the productivity growth due to more stringent government policies. Third, technological innovation mainly occurred in the coastal provinces, which have a lot of foreign direct investment. Finally, most coastal and central provinces achieved improvement in economic performance and environmental performance from 1992 to 2008. Meanwhile, west area provinces have a trade-off relationship between economic performance and environmental performance.

Our results suggest China's imbalanced progress on productivity growth and environmental protection across regions. It has important policy implications regarding differential policy at

regional level and environmental federalism. Innovations, FDI and patent applications are mainly concentrated in the coastal areas; this may also contribute to the overall efficiency improvement in the coastal areas.

On the other side, the western area is growing due to conventional economic inputs, while may at a loss of environmental efficiency. Given the gaps between the coastal and western regions, policy recommendations may need to consider more preferred policies to support innovative and high profit industries in the western region, such as more favored R&D and patent policies combined with tax-credit and subsidies to facilitate innovations and technology transfer from coastal area to central and western area.

In terms of federalism, considering the quite diverse characteristics of economic patterns and pollution performance, the central government should allow the local government more power to decide environmental policies to target regional needs. Considering the deteriorative environmental damages, environmental policies and regulations need to be strengthened in the western area to avoid “pollution haven” traps. The 11th and 12th Five Year Plan target were set mostly due to each province’ energy saving and emission abatement potentials and abilities, which in fact cause a gap in terms of targets.

In addition, other economic policies such as western development projects also provide tax

credit or subsidy incentives for more heavy pollution industries to shift from coastal area to western area. Therefore, even if the productivity and environmental performance improve in the coastal area, the overall improvements at the national level may be limited. Therefore, the economic policies and environmental policies need to be strengthened to achieve a more balanced production efficiency and environmental protection at the whole national level, and each region develop its own industries with comparative advantage. For instance, the western area can develop more green industries and renewable energy due to its abundant natural resource endowment or national park tourism.

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Table 1. Environmental policy in China

Year	Environmental regulations and projects
-1986	-The standard on discharge of industrial wastewater, waste gas and solid waste (1973)
	-Law on environmental protection (trial) was promulgated (1979)
	-Regulation on pollution levy (1982)
	-Marine environment protection law (1982, revised in 1999)
1986-1990	-Law on prevention and control of water pollution (1984, revised in 1996, 2008)
	-Law on prevention and control of air pollution (1987, revised 1995, 2000)
	-National environmental protection agency (NEPA) was upgrade as an organization directly under the state council (1988)
	-Law on environmental protection was amendment (1989)
1991-1995	-Implementation of the law on the water pollution prevention and control (1989)
	-Implementation of the law on the air pollution prevention and control (1991)
	-The second national conference on the prevention and control of industrial pollution proposed the notion of “Three shifts” (1993)
	-China’s agenda 21 (1994)
1996-2000	-Integrated emission standard of air pollutants (1997)
	-Emission standard of air pollutants for industrial kiln and furnace (1997)
	-Emission standard of air pollutants for coke oven (1997)
	-Implementation of the law of the people's republic of China on the water pollution prevention and control (2000)
	-The state council approved the plotting programs for acid rain control region and SO ₂ control region (enactment in 1998, implemented in 2002)
2001-2005	-Emission standard of air pollutants for coal-burning, oil-burning, gas-fired boiler (2001)
	-State environmental protection administration (SEPA) issued the interim measures on administration for discharge license of key water pollutants in Huai River and Tai lake, Basin (2001)
	-Technology policies on SO ₂ emission control from coal combustion (2002)
	-Law on the promotion of cleaner production (2003)
	-The state council issued the regulations on pollution levy (2003)
	-Emission standard of air pollutants for cement industry (2004)
	-SEPA issued the measures on preventing and controlling environmental pollution due to disused hazardous chemicals (2005)
2006-2010	-Renewable energy law (2006)
	-11 th five-year plan on energy conservation (20%) and SO ₂ emission control (10%) (2006)
	-11 th five-year plan of national water resources development (2006)
	-Chemical oxygen demand (COD) emission trading system – trial program (2007)
	-Measures on open environmental information (2008)
	-Circular economy promotion law (2008)

Table 2. Accumulated weighted TFP change and contribution effect by each variable from 1992 to 2008.

	Weighted TFP	Contribution effect of undesirable output (TFP _b)			Contribution effect of input (TFP _x)		Contribution effect of desirable output (TFP _y)
		Wastewater	Waste gas	Solid waste	Labor	Capital	Value added
Total	0.428	0.106	0.015	0.002	0.193	-0.016	0.128
Coastal area	0.319	0.084	0.019	0.010	0.149	-0.005	0.062
Central area	0.068	0.014	-0.000	-0.007	0.029	-0.007	0.038
West area	0.041	0.008	-0.004	-0.002	0.015	-0.005	0.028
p-value	0.155	0.258	0.176	0.322	0.135	0.211	0.836

*Weighted TFP change score is weighted regional average calculated by following equation.

Weighted average $TFP_t^{t+1} = \sum_j \{TFP_{tj}^{t+1} \times (\text{sale}_j^t / \sum_j \text{sale}_j^t)\}$ where j shows province and t shows year.

** p-value is estimated by nonparametric test for equality of multivariate density by Li et al. (2009).

Table 3. Accumulated FDI, patent application, patent granted, and innovators from 1992 to 2008.

	Innovator	Innovator _{Econ}	Innovator _{Env}	FDI	Patent application	Patent granted
Total	27 (5.48%)	28 (5.68%)	19 (3.85%)	346.2	130.25	68.16
Coastal area	19 (3.85%)	16 (3.25%)	15 (3.04%)	758.2	219.87	114.28
Central area	3 (0.61%)	3 (0.61%)	2 (0.41%)	145.9	84.78	43.59
West area	5 (1.01%)	9 (1.83%)	2 (0.41%)	53.3	41.03	22.93
p-value	0.78	0.915	0.566	0.07	0.160	0.165

*Innovator, Innovator_{Econ}, and Innovator_{Env} are accumulated count data how many times each regional province is identified as innovator out of 29 provinces over 17 years (i.e. $17 \times 29 = 493$). Number of 27 means 27 provinces are innovator and its share is $27/493 = 5.48\%$

**FDI (trillion yuan, 1995 price), patent application (1000 items), and patent granted (1000 items) are regional average.

***p-value is estimated by nonparametric test for equality of multivariate density by Li et al. (2009).

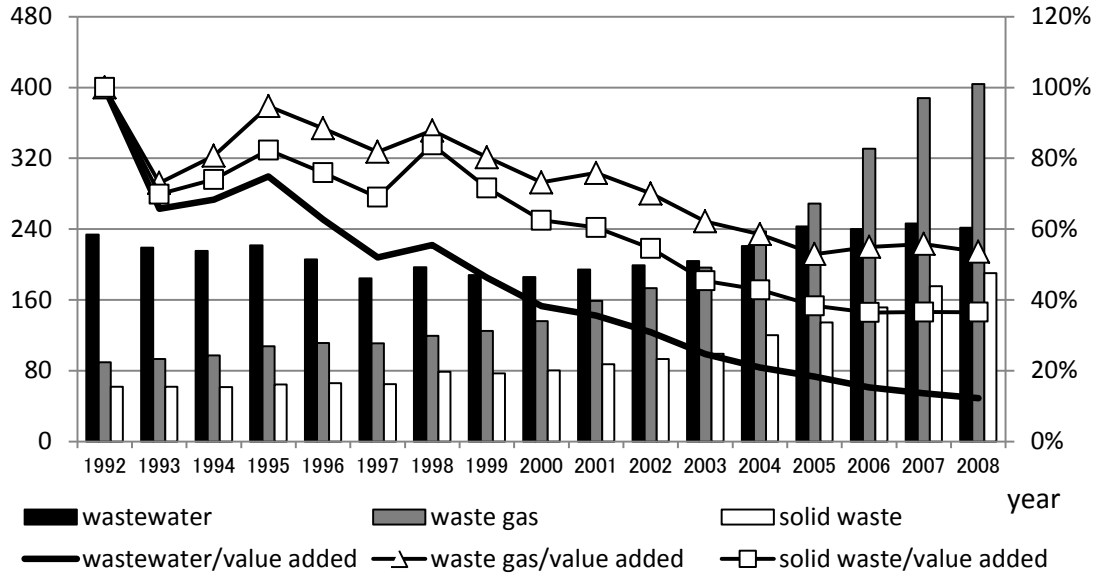


Figure 1. Pollution Emission and environmental efficiency in China
(Source: China Environmental Yearbook)

*Bar charts show the amount of pollution in China (left axis).

**Unit: wastewater: 100 million ton, waste gas: 100 billion m³, solid waste: 10 million ton.

***Line charts show the change of environmental efficiency (right axis, standardized as 1992=1).

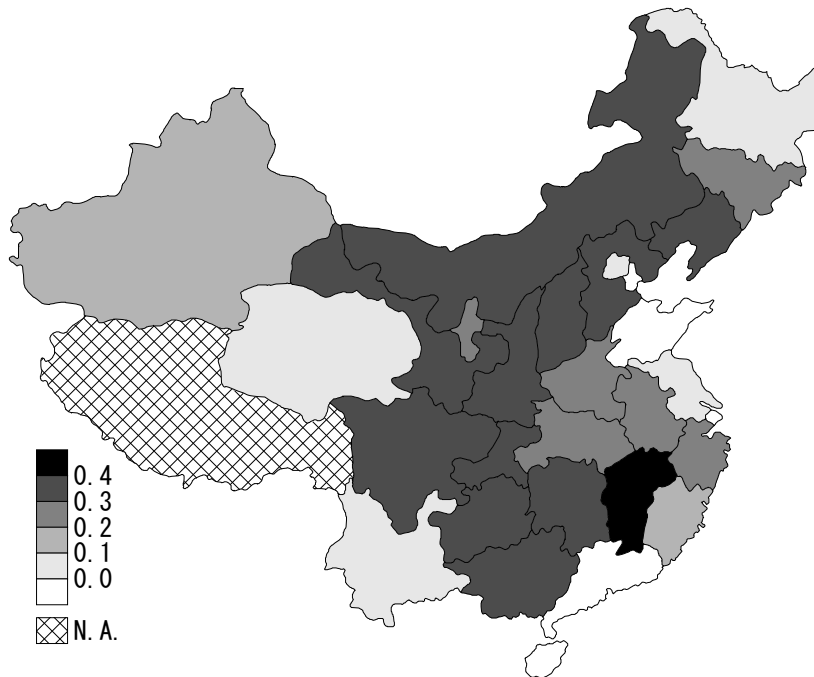


Figure 2. Average inefficiency score from 1992 to 2008 by province

*Average inefficiency score is calculated by following equation.

Average inefficiency score of province $j = \sum_{t=1992}^{2008} \{\bar{D}^t(x_j^t, y_j^t, b_j^t)\}$ where j shows province and t shows year.

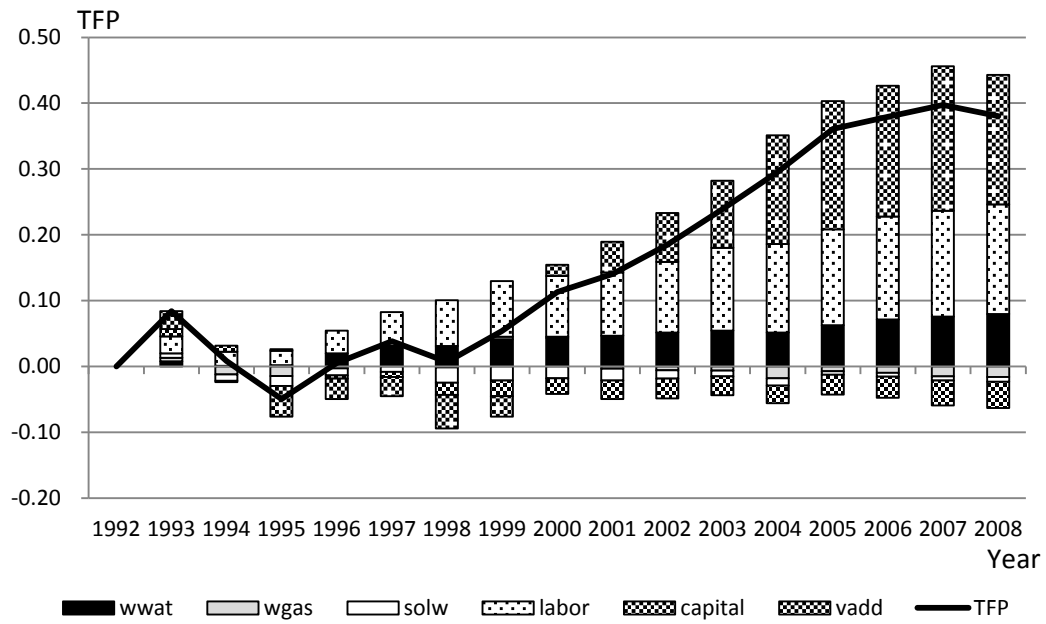


Figure 3. TFP and contribution effect of each variable (29 province average)

* Each score is regional average calculated by following equation.

$$TFP^t = \sum_{t=1992}^{t'-1} \sum_j (TFP_{tj}^{t+1}) / 29 \text{ where } j \text{ shows province, } t \text{ and } t' \text{ show year.}$$

We standardized $TFP^{1992}=0$.

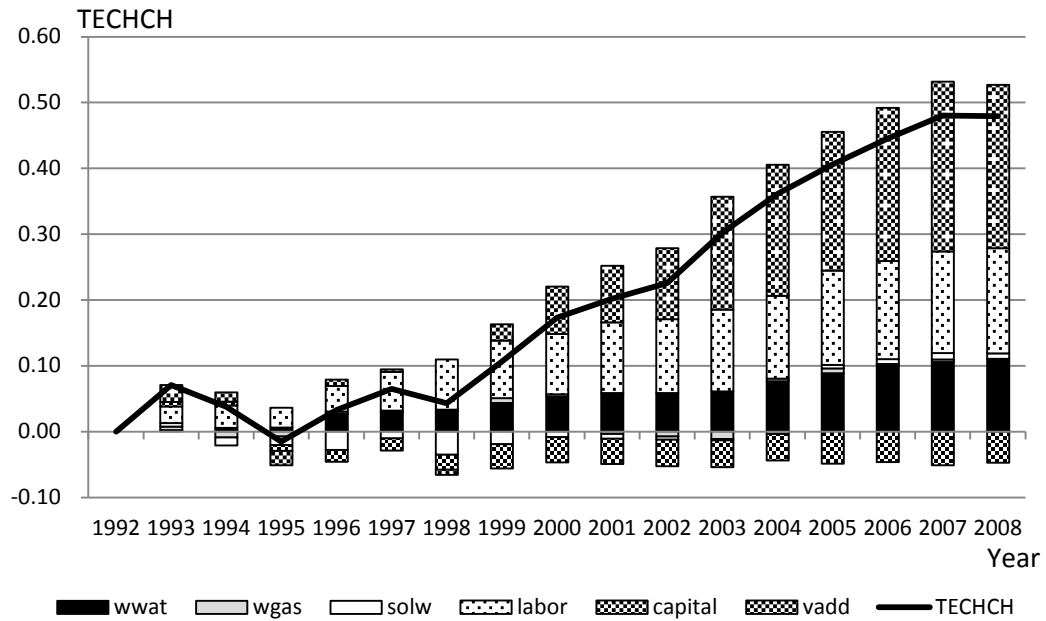


Figure 4. Result of TECHCH change and contribution effect of each variable (29 province average)

* Each score is regional average calculated by following equation.

$$TECHCH^t = \sum_{t=1992}^{t'-1} \sum_j (TECHCH_{t,j}^{t+1}) / 29 \text{ where } j \text{ shows province, } t \text{ and } t' \text{ show year.}$$

We standardized $TECHCH^{1992}=0$.

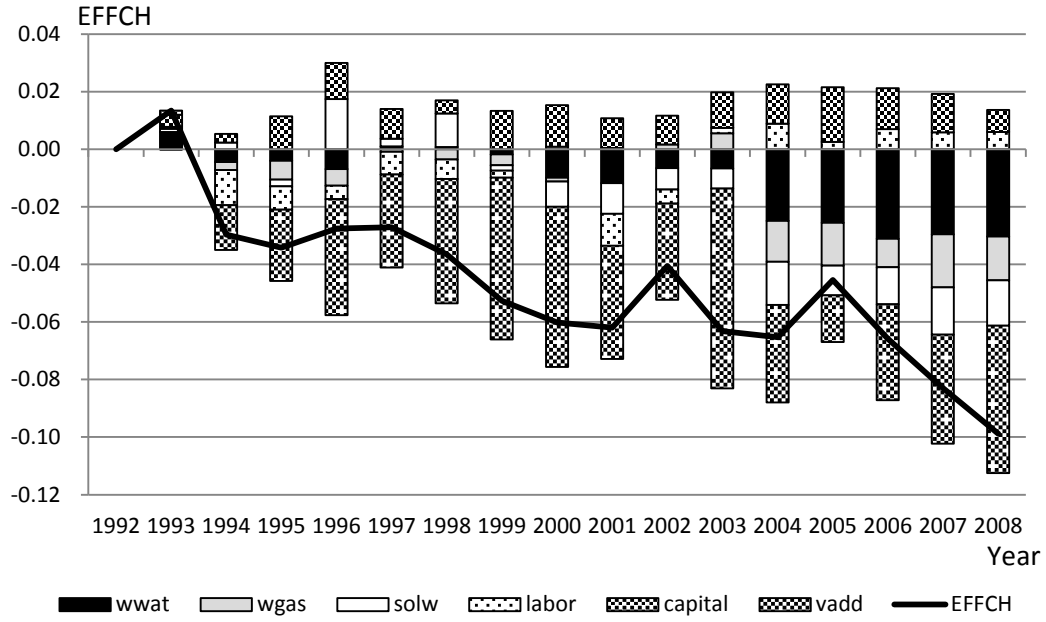


Figure 5. Result of EFFCH change and contribution effect of each variable (29 province average)

* Each score is regional average calculated by following equation.

$$EFFCH^t = \sum_{t=1992}^{t'-1} \sum_j (EFFCH_{t,j}^{t+1}) / 29 \text{ where } j \text{ shows province, } t \text{ and } t' \text{ show year.}$$

We standardized $EFFCH^{1992}=0$.

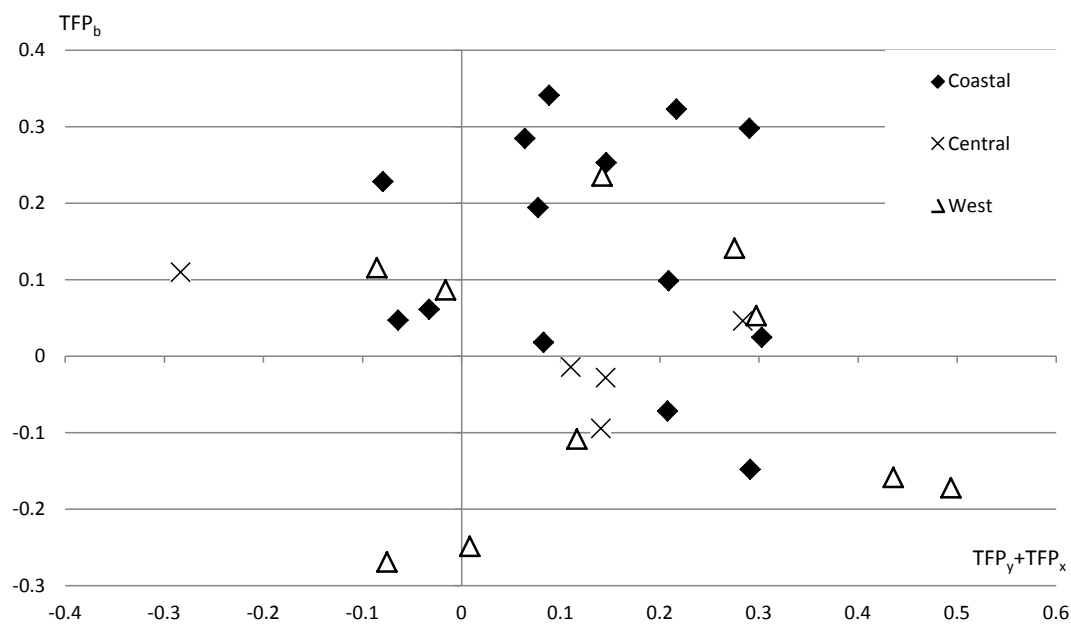


Figure 6. Scatter plot of accumulated TFP_b and $TFP_y + TFP_x$ by province.



Appendix. Provinces of China

Coastal area: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan.

Central area: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan.

West area: Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Inner Mongolia, Guangxi, Xinjiang.

Source: National Bureau of Statistics